On Participation in Group Chats on Twitter

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ABSTRACT
The success of a group depends on continued participation of its members through time. We study the factors that affect continued user participation in the context of educational Twitter chats. To predict whether a user that attended her first session in a particular Twitter chat group will return to the group, we build a 5F Model that captures five different factors: individual initiative, group characteristics, perceived receptivity, linguistic affinity, and geographical proximity. Through statistical data analysis of thirty Twitter chats over a two year period as well as a survey study, our work provides many insights about group dynamics in Twitter chats. We show similarities between Twitter chats and traditional groups such as the importance of social inclusion and linguistic similarity while also identifying important distinctions such as the insignificance of geographical proximity. We also show that informational support is more important than emotional support in educational Twitter chats, but this does not reduce the sense of community as suggested in earlier studies.

Categories and Subject Descriptors
H.0 [Information Systems]: General

Keywords
group dynamics; online communities; Twitter chats; speech codes theory; ostracism; information overload; mixed methods

1. INTRODUCTION
Human beings are social animals that are scarcely able to lead a solitary life (Baruch Spinoza, Ethics, IV, proposition 35:note). They interact and form relationships with others that endure from one encounter to another. A central theme in the study of human behavior is what makes a person become a member of a social group [16].

With the emergence of Web, many of our group interactions are moving on-line. One example of this move is the curious emergent phenomenon called Twitter chats. Twitter chats are public conversations, regularly held on Twitter on specific topics at designated times. For instance #engchat is a chat about English education held at 7-8pm EST on every Monday. During a chat session, the participants continuously interact on the designated topic by tweeting their opinions and marking their tweets with the hashtag of the particular chat group. While weekly groups like #engchat are the most common ones, there are others such as #mathchat that meet twice a week, #collegechat that meet bi-weekly or #edchat that are week-long conversations. Most of the chat groups also have dedicated blogs that provide various resources such as transcripts of past sessions and schedule of upcoming discussions. See [14] for a crowd-sourced list of Twitter chat groups.

The research question we investigate is what factors ensure continued individual participation in a Twitter chat. More specifically, our goal is to develop a model that can predict whether a person attending his/her first chat session in a particular Twitter chat group will return to the group. Figure 1 pictorially depicts the 5F Model we employ. Abstracting from the years of literature on group interactions in the physical off-line world [16, 23, 30, 34, 37, 40, 42, 45, 51], we identify five major factors that affect the participation of a person in a group: individual initiative, group characteristics, perceived receptivity, linguistic affinity, and geographical proximity. The Twitter specific measures corresponding to each of these factors are shown in boxes along the edges. For example, the number of tweets, the number of URLS in the tweets, the number of mentions and retweets contributed by the person during her first session provide indication of her individual initiative. Using data from thirty education-
related chat groups, we study the predictive power of these factors individually as well as collectively.

The paper proceeds as follows. We begin with a discussion of related work in §2. We then present the 5F Model in §3. The data sets used in the study are described in §4. We present the results of our statistical analysis in §5. This analysis delineates effectiveness of various Twitter measures in predicting the continued participation. We also carried out a survey to complement the statistical analysis. The findings from this survey are presented in §6. We conclude with a summary and directions for future work in §7.

2. RELATED WORK

Researchers in social sciences have long been studying group dynamics, focusing on different aspects such as formation, structure, cohesion or leadership [16]. In this paper, we focus on a key question relating to group dynamics: the ability of groups to sustain member relations. The social science literature on this topic is rich. Individual characteristics [30], group characteristics [16, 23, 40, 42, 45, 51], use of language [37] and geographical factors [34] are among the notions that have been studied and claimed to affect the individual-group interactions. Much of the classical social sciences research has been carried out for off-line groups.

With the advent of the Internet, groups and communities arose in the virtual world as well. Early research on online groups focused on structural characteristics of Usenet [7], listserv [35] and email groups [15]. With the arrival of next generation of social networks, the researchers had the opportunity to study group dynamics in online forums such as Yahoo groups [5], Google Groups [20], LiveJournal [3] and SecondLife [18]. Research questions addressed in the literature are as varied as the type of social networks studied and include topics such as structural properties [7], identification of sense of community [48], modeling individual behavior [5], use of language [20], identification of conversational themes [11], and evolution of the online communities [3].

The focus of our paper, i.e. the factors necessary for continued participation of online community members, have been studied in [1, 6, 8, 10]. In [1], authors study Usenet newsgroups and identify characteristics that increase the likelihood of a particular post receiving a reply and a poster coming back to newsgroups. They find that posters are less likely to get a reply if they were newcomers. Posting on topic, asking questions, and using less complex language are also identified as being important. In [8], authors analyze 200 responses to an open question regarding community loyalty in five Norwegian online groups and identify nine main reasons for decreasing participation over time: lack of interesting attendees, low quality content, low usability, harassment, time sink, low trust, over-commercialization, dissatisfaction with moderators and boring content. Chan et al. [10] identify three different forms of perceived recognition in a virtual community, namely identity, expertise and tangible recognition through an interpretive case study. Through surveys, they claim that members share their expertise because it makes them feel self-efficacious. In determining what makes an individual return to a particular community, Bateman et al. [6] study commitment theory originally introduced to study motivations behind voluntary work in online communities. Their survey based study reveals that affect-based, norm-based, and cost-based bonds collectively drive participation behavior in online communities.

In summary, related research on online communities mostly focused on a single factor in determining future participation while we introduce a framework that captures various factors. Also, we employ a mixed-method approach while the related work employs either a qualitative [8, 10] or quantitative [1, 6] solution but not both. With our approach, we can study group dynamics at scale as well as in detail. Finally, related work in online communities focused on asynchronous groups while we study Twitter chats that provide a much better proxy to synchronous face-to-face interactions.

3. 5F Model

We now present our 5F Model for studying continued individual participation in a Twitter chat group. The schematic we use is as follows. For each factor in the model, we first discuss the prior literature from which the factor has been abstracted. In some cases, we also identify subfactors that comprise the corresponding factor. We then discuss the Twitter specific measures for their computation.

3.1 Individual Initiative

3.1.1 Background

Certain people are more likely than others to seek out membership in groups due to differences in personal characteristics or motivations [16]. The big five theory [30] claims that people differ in five dimensions: extraversion, agreeableness, conscientiousness, neuroticism and openness. These differences are claimed to affect the likelihood of participating in groups. Of the five dimensions, extraversion is found to be a particularly influential determinant [16]. The importance of individual-level characteristics such as high-engagement and longevity in group interactions have also been observed in online communities such as Yahoo Groups [5].

3.1.2 Twitter Measures

In order to capture the importance of user-specific characteristics in group interactions, we consider the actions taken by the user at the first chat session that she attends. The independent variables that relate to individual initiative are:

1. usertweetcount denotes the number of tweets the user contributes to the session. This measure captures the extraversion dimension of the big five theory.

2. userurl denotes the number of urls the user contributes to the chat session. This variable acts as a proxy for informational contribution by the user.

3. usermentions is the total number of times the user mentions another (by using @). This measure captures how much the user engages in conversations.

4. userretweeted is the number of reweets by the newcomer user and captures the amount of information she found to be worth sharing with her followers.

3.2 Group Characteristics

3.2.1 Background

The experience that a user has in attending her first chat session depends on the context which is shaped by the actions of the others in the group. Therefore, these group-level
characteristics can affect the decision of the newcomer to return to the group. For instance, [1] shows that group-level factors can be predictive of future participation in online blogs. We next identify various group-level factors and study their significance. Four main themes studied are:

**Amount of Information**: Information overload refers to a person's state in which the overwhelming amount of information leads to communication inputs not being processed and utilized [40]. Information overload is especially important in the online context. For instance, in a recent work on Usenet newsgroups it has been shown that users are more likely to end active participation as the overloading of mass interaction increases [23].

**Conformity** Informational influence refers to group members using responses of others as reference points and informational resources [16]. This concept relates to conformity and has been observed in experimental studies in offline groups [42]. Conformity can result in coherent groups, eliminating controversies. Yet, too much conformity also throttles diverse perspective with reduced value for new users.

**Inter-member relations** Intermember relations play a critical role in determining whether a newcomer will come back to the group. Too much or too little dyadic interaction between group members can affect how a newcomer views the group [16]. The significance of inter-member relations has also been studied in [4] which focuses on individual arrival patterns in group discussions.

**Group Maturity** Various group formation theories (e.g. stages of group development [45]) assert that groups become cohesive over time where uncertainty about goals and roles are resolved. At the same time, such groups can become closed [51] to new members.

### 3.2 Twitter Measures

1. **sessiontweetcount** denotes the number of tweets in the chat session and captures the amount of information.
2. **sessionurl** is the number of urls shared in a chat session. This measure also captures the amount of information. We study sessionurl as a separate factor (in addition to sessiontweetcount) since tweets with URLs tend to be more informational than ordinary tweets.
3. **groupretweets** is the number of retweets in the chat session and captures conformity in the group.
4. **groupmentions** denotes the number of mentions in the chat session and quantifies intermember relations.
5. **groupmaturity** is the age of a group at a date D, and is computed as the number of sessions held until D.

For all these measures, we discount the tweets shared by the newcomer user for whom prediction is being made since the goal is to capture the context that the user interacts with rather than the context she creates.

### 3.3 Perceived Receptivity

#### 3.3.1 Background

Research in social sciences has established the importance of social inclusion in one's desire to affiliate with both traditional [31, 39, 44] and online [1, 24] groups. The importance of social inclusion is generally studied under ostracism which refers to the act of individuals or groups excluding or ignoring others [28, 49]. While some studies found that the excluded members respond by leaving the group [31, 39], others found increased desire to belong as a response [44].

### 3.3.2 Twitter Measures

We capture perceived receptivity through two variables:

1. ismentioned denotes whether the user is mentioned by at least one person in the chat session.
2. isretweeted indicates whether the user is retweeted.

### 3.4 Linguistic Affinity

#### 3.4.1 Background

Language is a key element in social interactions [2, 12, 21]. Speech Codes Theory [37] encapsulates this notion and states that "wherever there is a distinctive culture, there is to be found a distinctive speech code". This theory affirms individuals as either within or outside of the social structure by how in sync their language is with the language of the group. It has been shown that linguistic similarity has positive correlation with lasting dyadic relationships [21]. This effect has also been observed for group interactions in a recent study carried out in parallel to our study [13]. Another related work shows that the power differentials between individuals can be revealed by how much one echoes the linguistic style of the person they are responding to [12].

#### 3.4.2 Twitter Measures

We make use of Linguistic Inquiry and Word Count (LIWC) to compare linguistic markers between a user and a group. LIWC is a text analysis software that calculates the degree to which people use different categories of words across a wide array of texts [36]. LIWC uses positive or negative emotions, self-references, causal words, and 83 other dimensions and has been used in various studies [21].

We consider the set of tweets a user \( u_i \) shares in her first session as a text document and compute the value of each linguistic marker to obtain her LIWC-vector for that particular session. Similarly, we aggregate all the tweets from users other than \( u_i \) and compute the LIWC vector of the group. To identify the similarity, we use Pearson correlation measure that provides the degree of linear relationship between two vectors. This measure ranges from \(-1\) to \(+1\), with a large positive value indicating similar linguistic usage. We refer to this measure as liwccors in our model.

### 3.5 Geographic Proximity

#### 3.5.1 Background

Proximity Principle [34], a theory introduced in offline groups, states that people tend to join close by groups. Unlike the offline context, recent research suggests that online social networks can overcome this barrier [18, 27]. However, [38, 46] show that geography plays an important role in our use of language or choice of friends even in the online world. Hence, the role of geography is context-dependent and cannot be dismissed without investigation.

#### 3.5.2 Twitter Measures

To study the influence of geographical proximity, we calculate the mean distance of the user to everyone else in the
group. The location for each user is determined based on the location field of the user profile. We mine for the following patterns: latitude-longitude, \{city, region, country\}, \{city,region\}, \{city,country\}, \{region,country\} and country. For this purpose, we make use of data available from [29], which contains complete hierarchical information and coordinates for nearly 50,000 cities from all over the world. We convert all mined patterns to latitude-longitude pairs. For cities, we rely on the latitude-longitude points provided by the Gazetteer [29] and for regions and countries, we use the latitude-longitude of their most populated city. Given this data, the distance \(d\) (in meters) between two users \(u_i\) and \(u_j\) with locations \((\text{lat}_i, \text{lon}_i)\) and \((\text{lat}_j, \text{lon}_j)\) can be computed through Haversine formula [43]:

\[
\begin{align*}
    a &= (\sin(\text{dlat}/2))^2 + \cos(\text{lat}_i) \cdot \cos(\text{lat}_j) \cdot (\sin(\text{dlon}/2))^2 \\
    c &= 2 \cdot \arcsin(\min(1, \sqrt{a})) \\
    d &= R \cdot c
\end{align*}
\]

where \(\text{dlon} = \text{lon}_j - \text{lon}_i, \text{dlat} = \text{lat}_j - \text{lat}_i\) and \(R\) is the radius of the earth. The proximity of a user \(u_i\) to group \(g\) at a given session is computed as the mean distance between \(u_i\) and all other users \(u_j\) who attended that chat session. This measure is referred to as distance in our regression tasks.

4. DATA SET

4.1 Group Chats Studied

We examined over 100 education related chats appearing in a crowd-sourced list on the Web [14]. We chose to focus on education-related groups because of potential synergies with the current research in MOOCs [9]. In addition, relevant research underlines the informational power of Twitter for educators [17] and this power could potentially be enhanced through an improved community experience. Given the list in [14], we identify all tweets in each chat by capturing tweets with the corresponding hashtag. For this purpose, we analyze all Twitter updates from June 2010-July 2012. Next we filter the list to eliminate chats with the first identified tweet before September 2010 or after September 2011. This eliminates chats that can potentially pre-date our data collection or do not have a sufficient number of sessions.

Hashtags that represent these chats are also used outside the scheduled chat sessions. For instance, a user sharing a tweet that relates to teaching can use the hashtag \#teachchat even if the tweet is not shared during an actual session. In order to filter out such chatter, we rely on the bursty activity that is a general characteristic of hashtags that are associated with scheduled chat meet-ups. By identifying the hours of high activity (and including the preceding and following hours in order to capture the anticipation and wrap-up tweets), we capture the sessions for each chat. The hours of high activity are defined as those that have a \(\geq\)5-fold or more increase w.r.t. the earlier time frame. Our manual inspection has revealed that this simple technique accurately detects chat sessions. Next, we further filter the list of chats to only those with \(\geq 10\) sessions, which reduces the list of chats to 30. We also considered relying on advertised chat hours to capture chat sessions. However, this resulted in incorrect characterization as chat schedules get changed and various chat groups skip certain weeks, especially during summer.

Table 1 gives an overview of the chats studied. The columns of this table are: chat name, total number of tweets, total number of distinct users, number of sessions, and popular locations. Popular locations are identified by counting tweets from a given location and selecting the top 5 locations.

4.2 Salient Statistics

We next provide high level characterization of the chats studied as well as the users that participate in them.

Distribution of the number of users in and outside chat sessions: The distribution of the number of distinct users in each chat is provided as a CDF graph in Figure 2(a). The X-axis denotes the number of distinct users while the Y-axis denotes the fraction of the chats studied that have at most that many users. Here, we distinguish between user activity within and outside of chat sessions. The curve with + markers provides the distribution of users that participate in actual chat sessions while the other curve gives the distribution of users that tweeted same the hashtag at least once at some point of time (irrespective of whether the tweet was during a chat session). The difference between the two curves shows that a large number of users do not partici-
Table 1: Education Chats Studied

<table>
<thead>
<tr>
<th>Chat name</th>
<th>Discussion involved in</th>
<th># users</th>
<th># tweets</th>
<th># replies</th>
</tr>
</thead>
<tbody>
<tr>
<td>#globalclassroom</td>
<td>Global classroom project</td>
<td>6614</td>
<td>642</td>
<td>11</td>
</tr>
<tr>
<td>#techchat</td>
<td>School leadership</td>
<td>4543</td>
<td>702</td>
<td>15</td>
</tr>
<tr>
<td>#oippechats</td>
<td>Tech Integration</td>
<td>4231</td>
<td>745</td>
<td>15</td>
</tr>
<tr>
<td>#g提chat</td>
<td>Agricultural education</td>
<td>2387</td>
<td>284</td>
<td>14</td>
</tr>
<tr>
<td>#globalclassroom</td>
<td>Global classroom project</td>
<td>6614</td>
<td>642</td>
<td>11</td>
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<td>#techchat</td>
<td>School leadership</td>
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<td>#oippechats</td>
<td>Tech Integration</td>
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<td>15</td>
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<tr>
<td>#g提chat</td>
<td>Agricultural education</td>
<td>2387</td>
<td>284</td>
<td>14</td>
</tr>
</tbody>
</table>

Table 3: Geographical Distribution of Three Chats

- #globalclassroom: mostly in U.S., #5thchat is mostly in Ireland, and #techchat is mostly in Ireland.
- We note that #techchat is a chat formed by Irish educators to discuss education in Ireland.

5. STATISTICAL ANALYSIS

To predict whether a first-time visitor to a group will return for at least one more session in the future, we build individual models for the five factors (individual-initiative, group characteristics, perceived receptivity, linguistic affinity, and geographical proximity) as well as the unified SF Model. We use logistic regression [19] for statistical analysis and a Pseudo-R measure to compare the models. In particular, we employ the commonly used Nagelkerke $R^2$ Index [33] which can be computed as:

$$\frac{1-\frac{L(M_{\text{intercept}})}{L(M_{\text{null}})}}{1-\frac{L(M_{\text{intercept}})}{L(M_{\text{null}})}}$$

Here $N$ is the size of the data set, $L(M_{\text{null}})$ is the likelihood of the model given the data set, and $L(M_{\text{intercept}})$ is the likelihood of the null model. Larger Nagelkerke values indicate a better fit.

We performed this analysis at the individual chat group level as well as by combining tweets from all the chat groups. We present the results only for the combined case. The results for individual chat groups were similar, except for the geographical proximity model. We discuss those differences along with the discussion of the geographic proximity model.

5.1 Results

The regression results are summarized in Table 2. This table has four columns. The first column is the name of the

1. We also calculated Akaike Information Criterion (AIC) values for each model [19]. AIC results were consistent with the Pseudo-R results and are not included.
model and corresponds to one of the five factors. The second column lists the Twitter specific variables used for each of the corresponding factors. The third column consists of two subcolumns. The first subcolumn shows the coefficients of the corresponding explanatory variables in the individual-level models, whereas the second subcolumn gives the coefficients for the unified model. The third column gives the pseudo-R measure for the individual models. The pseudo-R value for the unified model is 0.14 and is shown at the bottom of the table. The statistically significant variables are marked with * for p-value < 0.05, ** for p-value < 0.01 and *** for p-value < 0.001.

**Individual Initiative Model:** The results show that all the variables except for usermentions are statistically significant. The number of tweets are positively correlated with returning to the chat group, emphasizing the predictive power of early interest exhibited by the user. The variable userurl is negatively correlated with returning to the group. One possible explanation for this result can be given as follows: For users that share a large number of urls, i.e. users that already acquire a certain level of knowledge, the added informational gain from chat sessions can be smaller, resulting in less incentive to attend future sessions.

The negative correlation for userretweets indicates that retweeting behavior can be used to distinguish real participants of chat groups from those that are merely retweeting the tweets of their friends who are attending a chat session. Consider the following illustrative scenario. Assume that user1 attending #1stchat shares a tweet “Check out article bit.ly/342dfser #1stchat”. This tweet is seen not only by the attendees of #1stchat but also the followers of user1. One such follower, say user2, can find the tweet interesting and retweet it. Here, user2 who appears to be attending his first #1stchat session may not return to this group.

**Group Characteristics Model:** Statistically significant variables are groupretweets, sessiontweetcount, sessionurl and groupmaturity. Capturing the significance of information overload, sessionurl and sessiontweetcount have negative correlation. The variable groupmaturity has negative correlation with the odds of come back, i.e. users that attempt to join more mature groups are less likely to return to the group. The results also indicate the significance of informational influence as demonstrated by the statistical significance and positive correlation of groupretweets. However we observe that the correlations of these factors are relatively mild. For instance, an increase of 1 retweet in group discussion decreases the log odds of come back by 0.0014. Pseudo-R(=0.03) values for this model are worse when compared to those of individual initiative model, showing that individual initiative factors are relatively better indicators of future participation.

**Perceived Receptivity Model:** Both ismentioned and isretweeted are statistically significant and positively correlated with returning to a group. Correlation measure is strong emphasizing the value of social inclusion. This result is in agreement with relevant research in other online communities [1, 24]. The Pseudo-R(=0.08) value for this model is the third best among the individual models.

**Linguistic Affinity Model:** Linguistic similarity is statistically significant and highly correlated with returning to a chat group. This finding supports our hypothesis and is in line with research in social sciences, particularly the speech codes theory. The highest Pseudo-R value for this model shows that the linguistic characteristics are the best indicators of future participation. In addition to evaluating linguistic similarity in an aggregate level, we also performed regression to identify the statistical significance of similarity among individual LIWC dimensions. Our results show that the use of conjunctions (p-value = 0.002, examples: but, and), discrepancy words (p-value=0.003, examples: should, would), causal words (p-value=0.03), WPS (words per sentence, p-value < 0.0001), punctuation letters (p-value=0.02) were among the most significant dimensions.

**Geographical Proximity Model:** We see that returning to a group is only mildly correlated with geographical proximity. An increased distance of 1km reduces the log odds of returning to the group by only 0.00005. Regression tasks performed per-chat group showed that geographical proximity is statistically significant for only seven educational Twitter chats. Two chats had positive correlation and five had negative correlation. For instance, #globalclassroom has positive correlation with the variable distance, indicating the positive effect of diverse locations in returning to the group. Such behavior is to be expected given the global goal of this particular group. Yet groups like #jedchat have negative correlation with increased distance. This group is on Jewish education and is mostly popular in Israel. Overall, the Pseudo-R value for this model is the worst among all models, showing that geographical characteristics are generally poor indicators of future participation.

**The Unified 5F Model:** In this model, we consider all the explanatory variables in conjunction, except geographic proximity (distance). The reason for omitting the latter is that we could determine the location of only a subset of users and this factor anyway turned out to have limited fit. As expected, this model has the largest Pseudo-R value. Each independent variable has similar explanatory trend as we observed with individual models.

### Table 2: Results of Statistical Analysis

<table>
<thead>
<tr>
<th>Factors</th>
<th>Variables</th>
<th>Coefficients</th>
<th>Pseudo-R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual Initiative</td>
<td>usermentions</td>
<td>-0.001</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>userretweets</td>
<td>-0.13***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sessionurl</td>
<td>-0.16***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>sessiontweetcount</td>
<td>-0.14***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>groupmaturity</td>
<td>-0.0001</td>
<td>0.04</td>
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<tr>
<td>Group Characteristics</td>
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<tr>
<td></td>
<td>groupretweets</td>
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</tr>
<tr>
<td></td>
<td>sessionurl</td>
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<td>sessiontweetcount</td>
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<td></td>
<td>groupmaturity</td>
<td>-0.01**</td>
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<tr>
<td>Perceived Receptivity</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>isretweeted</td>
<td>0.69***</td>
<td>0.08</td>
</tr>
<tr>
<td>Linguistic Affinity</td>
<td>tweets</td>
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<td>0.1</td>
</tr>
<tr>
<td>Geographical Proximity</td>
<td>distance</td>
<td>-0.00005***</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Pseudo-R for the unified 5F model ≤ 0.14

5.2 Discussion

Our results show various parallels between Twitter chats and other offline and online groups. For instance, the importance of social inclusion that has been identified in both offline and online groups [28, 31, 39, 44, 49] is also significant in Twitter chats; newcomers that are mentioned or retweeted by others in a chat session are much more likely to come back to the chat group. Also, the use of language plays a critical role; newcomers that have a similar language...
to a given group are likely to continue participation. While the similar use of words related to education might be anticipated to effect participation in educational Twitter chats, our results go beyond this finding. We show that similarity in the language along dimensions such as sentence complexity (words per sentence), causal words, or even punctuation letters reveal much about group interactions. In other words, language defines individuals as either insiders or outsiders of groups in Twitter chats as suggested by speech codes theory [37].

We also found that users are less likely to return to established groups, i.e. groups that have held a large number of chat sessions, indicating that groups become closed to new members over time [45]. The total number of tweets and urls shared in the chat session also decrease the likelihood of returning to a group. While the idea of more information driving away participants can sound counter-intuitive at first, it can in fact be explained by the effects of information overload [23, 40]. The large scale and synchronous nature of discussions held in Twitter chats likely magnify the effects of information overload that is already prevalent in asynchronous online communities [23]. Our survey study also supports this finding as we will demonstrate in §6.

One major distinction of Twitter chats from traditional groups is the insignificance of geographical proximity. Unlike offline groups [34], we show that there is no correlation between geography and group affiliation for most Twitter chats, the exceptions being chats organized around local topics (e.g. #jewishchat on Jewish education in Israel). In fact, geographical diversity is considered as the most important advantage of Twitter chats as demonstrated in §6.

Turning to the relative importance of the factors, the best individual models to capture continued user participation in order are: linguistic affinity, individual initiative, perceived receptivity, group characteristics and geographical proximity. This ordering reveals distinctions of Twitter chats from other groups studied in the literature. For instance, related research claims that individuals are initially drawn to online communities by a desire to interact with like-minded others but whether they return is significantly influenced by the content of the community [6]. Yet, our analysis shows that individual characteristics are better indicators of future participation than group characteristics. In addition, past research emphasized the value of perceived receptivity as the dominant factor [10] while we find it to be the third statistically determining factor.

The impact of linguistic similarity in group participation is largely unexplored, yet we found this factor to be the best predictor of future participation. We note that the 140 character limit that Twitter enforces for tweets likely introduces added challenges to the newcomers as this limit drives participants to use shorthand descriptions for various notions which can be confusing for the newcomers. This finding is also supported by our survey study.

### 6. USER SURVEY

We complemented the results from the statistical data analysis with a user survey to directly understand from users involved in Twitter chats their attitudes towards these chats. We circulated an online survey of 26 questions (through Twitter) to users that participated in education chats. Table 3 lists the questions asked in our user survey. The options of multiple choice questions with one possible answer are marked as (a), (b), and so on. When more than one option can apply, they are marked as (i), (ii), and so on. The survey was publicized in educational Twitter chats through the hashtag of each chat group studied. Respondents of the survey were encouraged to share the survey with their Twitter followers. In all, sixty users responded to our survey.

Fifty of the survey participants identified themselves as educators. One identified himself as a student. Three participants stated that they were both an educator and a student. Three stated that they were both an educator and a parent of a student. Fourteen, nineteen, twenty three and four of the survey participants stated that they participate in one, two, three-to-five and more than five education chats respectively. The number of distinct Twitter education chats participated by our survey respondents is sixty six. ²

### 6.1 Findings

The survey had three main parts, addressing questions related to: (1) usage, advantages and disadvantages, (2) sense of community and responsibility, and (3) evolution of participation. We discuss findings for these segments next.

#### Usage, Advantages and Disadvantages

Table 4 shows the number of survey participants who identified a particular characteristic of Twitter chats. The results show that most users value the informational support provided in Twitter chats. The ability of Twitter to connect people with others is another important theme. The results show an interesting distinction between educational Twitter chats and other online groups [47, 48] for which emotional support is found to be more significant. In fact, in past research, sense of community is found to be negatively correlated with informational support [48]. Yet, as we will discuss later, sense of community is strong in Twitter chats despite the fact that informational support is more dominant than emotional support.

When asked to identify the advantages of Twitter chats compared to face-to-face meetings and online groups, the survey respondents gravitated towards similar high level observations even though they were not provided with a set of predefined options. The results are presented in Table 5. The most common advantage identified is the diversity in backgrounds and geographical locations of chat participants.

²Since the population in our survey does not constitute a statistically sound representative sample, the reader should view the findings as anecdotal. We also note the possibility of positive bias towards Twitter groups since those who left them are less likely to have responded to the survey. The results are instructive, nonetheless.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>No of survey respondents</th>
</tr>
</thead>
<tbody>
<tr>
<td>The sense of belonging</td>
<td>26</td>
</tr>
<tr>
<td>Emotional Support</td>
<td>17</td>
</tr>
<tr>
<td>Informational Support</td>
<td>57</td>
</tr>
<tr>
<td>Instrumental Support</td>
<td>36</td>
</tr>
<tr>
<td>Networking with friends/colleagues</td>
<td>46</td>
</tr>
<tr>
<td>Making new friendship/professional connections</td>
<td>41</td>
</tr>
</tbody>
</table>

Table 4: Uses of Twitter Education Chats
This finding is in line with the result of our data analysis that
showed that geography is not a limiting factor for most chat
groups. One interesting advantage identified by the survey
respondents notes a significant difference between face-to-
face and Twitter groups: the ability to record group
discussions.

Twenty six survey participants provided disadvantages of
Twitter chats. Three most dominant themes are listed in
Table 6. Interestingly, lack of face-to-face interactions was
only at the third place while it has been found to be the
dominant factor in the literature [22]. Instead, the most im-
portant disadvantage is the pace and amount of information.
This result is a direct implication of the unique character-
istic of Twitter chats since unlike other online groups, they
introduce the added challenge of interacting with a large
crowd in a synchronous manner. We note that three people
indicated that there were no disadvantages of Twitter chats.
The rest (five survey participants) touched on various top-
ics such as the public characteristic of conversations limiting
negative discussions or the timing of the chats.

Table 3: Survey Questions

<table>
<thead>
<tr>
<th>No of survey respondents</th>
<th>Advantage</th>
</tr>
</thead>
<tbody>
<tr>
<td>9</td>
<td>Diversity in backgrounds and geography</td>
</tr>
<tr>
<td>5</td>
<td>Ease of sharing information</td>
</tr>
<tr>
<td>9</td>
<td>Ability to archive and search older chats</td>
</tr>
<tr>
<td>4</td>
<td>Public form and equality</td>
</tr>
</tbody>
</table>

Table 5: Advantages of Twitter Chats

<table>
<thead>
<tr>
<th>No of survey respondents</th>
<th>Disadvantage</th>
</tr>
</thead>
<tbody>
<tr>
<td>9</td>
<td>Face and Amount of Information Flow</td>
</tr>
<tr>
<td>6</td>
<td>Twitter syntax</td>
</tr>
<tr>
<td>5</td>
<td>Lack of face-to-face interactions</td>
</tr>
</tbody>
</table>
We call participants in Satchat the #satchat family.

On the downside, as a group gets more mature and connected, it can also become closed to new members as demonstrated by the responses of two survey participants:

... tends to become very cliquey and the key players over time use more and more “insider” references or hold more and more side discussions during the chat.

I feel as though a hierarchy has developed and there are times where people within that hierarchy at times will dismiss other ideas.

These write-ins support the results presented in §5 that show the negative correlation of group maturity with returning to a group.

Thirty nine survey participants stated that they feel a responsibility to the community to participate in chat sessions while seventeen stated that they did not. Drawing on commitment theory [32] that was initially introduced to reason about volunteer behavior, we considered the responses of the survey participants to identify behavior indicative of three types of commitment: affect-based which refers to individual’s emotional attachment to a group, norm-based which captures individual’s felt sense of obligation and cost-based which refers to individual’s awareness of the costs associated with leaving an organization. We found norm-based and cost-based bonds to be prevalent. Examples of cost-based bonds can be seen in users that see Twitter chats as a valuable utility and are driven to participate due to its benefits:

People “lurk and learn” all the time. You go if you want - it’s YOUR PD, when and how YOU want it.

Although the open form of Twitter chats allows for “lurking” behavior, there is still a large number of dedicated members that are driven by norm-based bonds. These participants view reciprocity as an important notion and feel obligated to participate as demonstrated by the following quotes:

I take others’ ideas, so it’s only right I respond in kind.

I know that I appreciate learning from others and sharing ideas, so I think it’s my duty to reciprocate.

Unlike related work [6], we have not observed affect-based bonds to be prevalent in Twitter chats. This outcome is consistent with the dominance of informational support over emotional support.

Origins and Evolution: Fifteen respondents discovered their primary education chat group through another Twitter chat. Seventeen became aware of the existence of such groups through general Twitter usage. Nine stated that they created/co-created their chat groups. While research in online social networks focuses on the effectiveness of social networks to spread information [25], our survey revealed that a notable fraction of Twitter users discovered their primary educational Twitter chat through exogenous channels (nine through education related forums/blogs, six through offline connections and three through emails).

The four main reasons listed by the survey respondents as the initial goals/reasons for participating in Twitter chats were: to explore, out of curiosity (27), to learn new information/tools/methods (28), to make new connections (17), and for the sense of belonging (9). These reasons are more information-based rather than social-connection-based unlike related work [41].

Thirty respondents stated that their view of the chat group changed over time; with most people stating that it became easier for them to follow conversations that caused them to change their view. Only ten respondents stated their positioning and responsibilities had changed over time. Two stated that they had become less active, with one of them ending active participation. Eight respondents had become more integral to groups over time taking on more responsibilities. The users with decreased participation mentioned the unwelcoming environment. One stated:

I was welcomed and greeted warmly - I went back - it wasn’t repeated - but the conversation was worth it, so I lurk and read archives.

This quote reinforces the importance of perceived receptivity which was found to be important in our statistical data analysis (§5).

Feedback: We also asked the survey respondents how the quality of conversations can be improved in Twitter chats. There were fourteen responses with suggestions. Most replies highlight problems that can be addressed through technological solutions. Some common themes were: “Once a tweet is retweeted in the chat, protocol should be that no one else retweets it. I find multiple retweets to very frustrating and clutters up the feed.”, “All chats should be archived”, “A central place to find other chats that are on topic would be helpful.”

Some comments go to the nature of the groups: “Allow differing opinions to be more than fodder for side-chats.”, “Sometimes chats can use a tone that is condescending to new people. Please don’t use terms like “newbies!””, “More educators need to get on the bus and join in on twitter.”, “A few chats could be better-prepared by organisers: eg greater publicity (reminders in advance), more guiding questions and more resources”, “If people are looking for professional development on Twitter, they need to be willing to be challenged and respond, rather than run away with hurt feelings that leave them unchanged.”

6.2 Discussion

Our survey study marks various distinctions between Twitter chats and other online groups and face-to-face discussions. For one, informational support has been found to be more important to Twitter chat users than emotional support. Although related work suggests that informational support is negatively correlated with the sense of community [48], the sense of community is very strong in Twitter chats. In fact, its members communicate with one another outside chat sessions much more than expected from the literature [41]. Disadvantages identified by the survey respondents also mark an interesting distinction between Twitter chats and other online groups. While for other online communities, the lack of face-to-face interactions is a main disadvantage, Twitter chat users focus on the content. More
specifically, due to the synchronous and open nature of Twitter, the pace of information is the biggest challenge of Twitter chats.

We have also observed that the survey results reinforce most findings presented in Section 5. The importance of social inclusion is observed from the responses of two survey participants that reduced (one ending) their participation due to the lack of receptivity. Groups becoming closed to new members over time (as captured by groupmaturity in our model) is seen anecdotally in survey results. The geographical diversity listed as an advantage also indicates that geography is not a limiting factor for Twitter chats.

7. CONCLUSIONS AND FUTURE WORK

What makes a person become a member of a particular group? We addressed this question in the context of Twitter chats which are time-bound synchronous group interactions carried out in real time on a focused topic on Twitter. We developed 5F Model that predicts whether a person attending her first chat session in a particular Twitter chat group will return to the group. This model considers five different classes of factors: individual-initiative, group characteristics, perceived receptivity, linguistic affinity and geographical proximity, building upon findings from prior research on asynchronous online groups and communities.

We performed statistical data analysis for thirty educational Twitter chats involving 71411 users and 730944 tweets over a period of two years. Analysis was performed to identify the significance of separate models for each of the five factors listed above as well as the unified 5F Model. We also complemented the results of statistical analysis with a survey study.

Our results show that users are more likely to return to Twitter chats that mention or retweet them, stressing the importance of social inclusion. Unlike offline groups, we find that for most Twitter chat groups, geographical proximity is not a limiting factor for a user to affiliate with a group. In addition, we show that informational support is more important than emotional support in educational Twitter chats. Unlike what is suggested by research in other online communities, the sense of community in Twitter chats is very strong despite this finding. Given the synchronous nature and popularity of Twitter chats, we also observed that information overload was a significant challenge. Interestingly, our results indicate that the best predictor for future participation is linguistic affinity, as opposed to individual or group characteristics that the literature mostly focuses on.

To the best of our knowledge, this is the first work to consider group dynamics questions in Twitter chats. The findings of this study provide various insights for Twitter chat organizers. For instance, creating a welcoming environment and providing ways to alleviate the unpleasant effects of information overload are two paths to long-lasting user participation in Twitter chats.

As future work, we aim to extend our work on educational Twitter chats to chats held on other topics. This would allow us to identify the generalizability of the findings in educational chats and determine characteristics that are unique to them. While we focused on the first interactions of participants with Twitter chat groups, it is also important to identify how individual-group interactions evolve over time. For this purpose, we aim to study the evolution of Twitter chats, identify different types of chat participants and quantify their contributions to the success of Twitter groups over time.

8. ACKNOWLEDGMENTS

We would like to thank James Cook, Krishnaram Kenthapadi, and Nina Mishra for bringing the Twitter chat phenomenon to our attention. We would also like to thank Nina Mishra and Jed Brubaker for the insightful discussions.

9. REFERENCES